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Software Module Clustering as a Multi-Objective Search Problem

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Abstract—Software module clustering is the problem of automatically organizing software units into modules to improve program structure. There has been a great deal of recent interest in search-based formulations of this problem in which module boundaries are identified by automated search, guided by a fitness function that captures the twin objectives of high cohesion and low coupling in a single-objective fitness function. This paper introduces two novel multi-objective formulations of the software module clustering problem, in which several different objectives (including cohesion and coupling) are represented separately. In order to evaluate the effectiveness of the multi-objective approach, a set of experiments was performed on 17 real-world module clustering problems. The results of this empirical study provide strong evidence to support the claim that the multi-objective approach produces significantly better solutions than the existing single-objective approach.

Index Terms—SBSE, module clustering, multi-objective optimization, evolutionary computation.

1 Introduction

Software module clustering is an important and challenging problem in software engineering. It is widely believed that a well-modularized software system is easier to develop and maintain [8], [27], [29]. Typically, a good module structure is regarded as one that has a high degree of cohesion and a low degree of coupling [8], [27], [29]. Sadly, as software evolves, its modular structure tends to degrade [17], necessitating a process of restructuring to regain the cognitive coherence of previous incarnations. This paper is concerned with automated techniques for suggesting software clusterings, delimiting boundaries between modules that maximize cohesion while minimizing coupling.

Many authors have considered the implications of software modularization on many software engineering concerns. Badly modularized software is widely regarded as a source of problems for comprehension, increasing the time for ongoing maintenance and testing [27], [29], [31]. The use of cohesion and coupling to assess module structure was first popularized by the work of Constantine and Yourdon [8], who introduced a seven-point scale of cohesion and coupling measurement. These levels of cohesion and their measurement have formed the topic of much work which has sought to define metrics to compute them and to assess their impact on software development [1], [3], [25], [14].

There are many ways to approach the module clustering problem. Following Mancoridis et al., who first suggested the search-based approach to module clustering [20], this paper follows the search-based approach. In the search-based approach, the attributes of a good modular decomposition are formulated as objectives, the evaluation of which as a "fitness function" guides a search-based optimization algorithm.

The module clustering problem is essentially a graph-partitioning problem which is known to be NP-hard [11], [20], so there is no efficient algorithm for solving the problem to its exact optimum unless P=NP [11]. This observation provided the motivation for previous work on this problem, which aimed at finding a near-optimal solution within a reasonable amount of time.

Without exception, all previous work on the module clustering problem [20], [19], [23], [10], [22], [18], [15] and other work inspired by it [7] has used a single-objective formulation of the problem. That is, the twin objectives of high cohesion and low coupling have been combined into a single objective called Modularization Quality (MQ) (using weights applied to the measurements of cohesion and coupling). In all studies reported upon to date, the hill-climbing algorithm has performed the best in terms of both the quality of solutions found (measured by MQ values) and in terms of the execution time required to compute them.

However, despite its success, this single-objective approach raises the uncomfortable question:

> How much cohesiveness should be sacrificed for an improvement in coupling?

This question, and its converse, are uncomfortable for several reasons. Such questions ignore the fact that the measurements of cohesion and coupling are inherently ordinal scale metrics and, so, even attempting to pose such a question contradicts sound measurement theory [28]. Even if it were possible to compare the cohesion and coupling measurements on an interval or ratio scale, there is the additional problem that this essentially requires the mistaken comparison of "applies and oranges"; it is not possible to normalize coupling and cohesion in a meaningful way so that each can be measured in comparable

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units nor is it easy to decide upon the relative weights that should be applied to each.

There is a natural tension between the objective of achieving low coupling and the objective of achieving high cohesion when defining module boundaries. These two aspects of the system will often be in conflict. Therefore, any attempt to conflate cohesion and coupling into a single objective may yield suboptimal results. In similar software engineering scenarios in which there are a set of two or more possibly conflicting objectives, a natural step is the use of Pareto optimality [2], [30], [32].

This paper introduces the first Pareto optimal multi-objective formulation of automated software module clustering, presenting results that show how this approach can yield superior results to those obtained by the single-objective formulation. The paper also explores the ways in which the richer solution space afforded by a Pareto optimal approach can be used to yield insight into the choices available to the software engineer faced with the task of restructuring to improve modular cohesion and coupling.

The primary contributions of the paper are as follows:

1. The multi-objective paradigm for automated software module clustering is introduced. Two formulations of the multiple objective approach are studied: the Equal-size Cluster Approach (ECA) and the Maximizing Cluster Approach (MCA).
2. A novel two-archive Pareto optimal genetic algorithm is introduced for the solution of multi-objective module clustering.
3. An empirical study into the effectiveness and performance of the single and multi-objective formulations of the problem is presented. The primary findings of the study are:

   a. The multi-objective approach is able to produce very strong results for both weighted and unweighted Module Dependency Graphs. For weighted Module Dependency Graphs, it produces better results than the single-objective hill-climbing approach, even when measured against the hill climber's own fitness function (MQ).
   b. Though the multi-objective approach performs well, there are still cases where the single-objective approach can produce good results for unweighted graphs, indicating that hybrid approaches may be worthy of further consideration for unweighted graphs.
   c. For producing low cohesion and coupling, the Equal-size Cluster Approach to the multi-objective problem produces the best results overall.
   d. The two multi-objective search formulations and the existing single-objective formulation search different parts of the solution space.
   e. Though the multi-objective formulations produce far better results, they do so at a computational cost; two orders of magnitude more effort are required in order to achieve the better results using the multi-objective approach. However, the paper argues that, in many practical situations, the additional time required for better results is both available and also a worthwhile cost for the additional quality of the modularizations identified.

The rest of this paper is organized as follows: Section 2 presents background material and related work on software module clustering. Section 3 introduces the multi-objective paradigm of module clustering. Section 4 describes the research questions and experiments performed in the empirical study that aims to assess the effectiveness and performance of the multi-objective approach compared to the single-objective formulation. Section 5 presents the findings of the empirical study and answers to the research questions. Section 6 discusses the ways in which this work could be used in order to assist the practicing software engineer. Section 7 considers threats to validity, while Section 8 concludes.

2 Automated Software Module Clustering

Many metaheuristic methods have been successfully applied to software module clustering. The field was established by the seminal work of the Drexel group [20]. In this work, hill climbing was the primary search technique [20], leading to the development of a tool called Bunch [19] for automated software module clustering.

Several other metaheuristic search technologies have been applied, including simulated annealing and genetic algorithms [13], [18], [22]. However, these experiments have all shown that other techniques are outperformed in both result quality and execution time by hill climbing.

In order to formulate software engineering problems as search problems, the representation and fitness function need to be defined [6], [12]. In the case of module clustering, previous work has used the Module Dependency Graph (MDG) as a representation of the problem [20]. The MDG is represented as a simple array mapping modules (array indices) to clusters (array elements used to identify clusters) [20]. The array $\{2, 2, 3, 2, 4, 4, 2, 3\}$ denotes a clustering of eight modules into three clusters, identified by the numbers 2, 3, and 4. For example, modules numbered 0, 1, 3, and 6 are all located in the same cluster (which is numbered 2). The choice of numbers of module identifier is arbitrary, so this clustering is equivalent to $\{1, 1, 3, 1, 4, 4, 1, 3\}$ and $\{3, 3, 2, 3, 4, 4, 3, 2\}$.

The MDG can thus be thought of as a graph in which modules are the nodes and their relationships are the edges. Edges can be weighted, to indicate a strength of relationship, or unweighted, merely to indicate the presence or absence of a relationship. As will be seen, the algorithms studied in this paper differ noticeably in their performance on weighted MDGs when compared to the results obtained for unweighted MDGs and so this distinction between weighted and unweighted turns out to be an important aspect of problem characterization. The choice of what constitutes a "module" and what precisely can count as a "relationship" are parameters to the approach. In previous work (and in the present paper), a module is taken to be a file and a relationship is an inclusion of reference relationship between files (e.g., a method invocation).

In order to guide the search toward a better modularization, it is necessary to capture this notion of a "better" modularization. Traditionally, single-objective approaches used the Modularization Quality measure, introduced by

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Mancoridis et al. [20]. The intra-edges are those for which the source and target of the edge lie inside the same cluster. The inter-edges are those for which the source and target lie in distinct clusters. MQ is the sum of the ratio of intra-edges and inter-edges in each cluster, called the Modularization Factor (MF_k) for cluster k. MF_k can be defined as follows:

$$MF_k = \begin{cases} 0, & \text{if } i = 0, \\ \frac{i}{i+\frac{1}{2}j}, & \text{if } i > 0, \end{cases} \tag{1}$$

where i is the weight of intra-edges and j is that of inter-edges, that is, j is the sum of edge weights for all edges that originate or terminate in cluster k. The reason for the occurrence of the term $\frac{1}{2}j$ in the above equation (rather than merely j) is to split the penalty of the inter-edge across the two clusters that connected by that edge. If the MDG is unweighted, then the weights are set to 1.

The MQ can be calculated in terms of MF as

$$MQ = \sum_{k=1}^{n} MF_k, \tag{2}$$

where n is the number of clusters.

The goal of MQ is to limit excessive coupling, but not to eliminate coupling altogether. That is, if we simply regard coupling as bad, then a "perfect" solution would have a single module cluster containing all modules. Such a solution would have zero coupling. However, this is not an ideal solution because the module would not have the best possible cohesion. The MQ measure attempts to find a balance between coupling and cohesion by combining them into a single measurement. The values produced by MQ may be arbitrarily large because the value is a sum over the number of clusters present in a solution and so the MQ function is not a metric. The aim is to reward increased cohesion with a higher MQ score and to punish increased coupling with a lower MQ score.

In order to handle weighted and unweighted graphs using the same approach, an unweighted graph is essentially treated as a weighted graph in which all edges have an identical weight.

3 Software Module Clustering as a Multi-Objective Problem

Existing approaches to the twin objectives of high cohesion and low coupling have combined these two objectives into a single-objective function, with all of the drawbacks to which the introduction of this paper referred. Pareto optimality is an alternative approach to handling multiple objectives that retains the character of the problem as a multi-objective problem. Using Pareto optimality, it is not possible to measure "how much" better one solution is than another, merely to determine whether one solution is better than another. In this way, Pareto optimality combines a set of measurements into a single ordinal scale metric.

The fitness $F(\overline{x})$ of a candidate solution vector, $\overline{x}$, is defined in terms of the fitness ascribed to $\overline{x}$ by each of the constituent fitness functions, f_i, but this does not yield a single number for an "aggregated fitness." Rather, a relationship is defined on candidate solution vectors that define when one solution is superior to another. Under the Pareto interpretation of combined fitness, "no overall fitness improvement occurs no matter how much almost all of the fitness functions improve, should they do so at the slightest expense of any one of their number" [12]. More formally, the relation is defined as follows:

$$F(\overline{x_1}) > F(\overline{x_2})$$
$$\Leftrightarrow$$
$$\forall i. f_i(\overline{x_1}) \geq f_i(\overline{x_2}) \land \exists i. f_i(\overline{x_1}) > f_i(\overline{x_2}).$$

That is, solution $\overline{x_1}$ is better than another $\overline{x_2}$ if it is better according to at least one of the individual fitness functions and no worse according to all of the others. Such a solution $\overline{x_1}$ is said to "dominate" $\overline{x_2}$. If no element of a set $\overline{X}$ dominates some solution $\overline{x}$, then $\overline{x}$ is said to be nondominated by $\overline{X}$.

A Pareto optimal search yields a set of solutions that are mutually nondominating and which form an approximation to the Pareto front. The Pareto front is the set of elements that are not dominated by any possible element of the solution space. The Pareto front thus denotes the best results achievable; it is the equivalent of the set of globally optimal points in a single-objective search. As with the single-objective formulation, it is not possible to guarantee to locate this globally optimal solution set, merely to attempt to approximate it as closely as possible.

Each set of objectives leads to a different multi-objective formulation of the problem. In this paper, two sets of objectives will be considered: The Maximizing Cluster Approach and the Equal-size Cluster Approach. These are explained below:

3.1 The Maximizing Cluster Approach

The Maximizing Cluster Approach uses the following set of objectives:

- the sum of intra-edges of all clusters (maximizing),
- the sum of inter-edges of all clusters (minimizing),
- the number of clusters (maximizing),
- MQ (maximizing),
- the number of isolated clusters (minimizing).

The inter-edges, the intra-edges, and the MQ are used to measure the quality of the system partitioned. An isolated cluster is a cluster that contains only one module. Experience and intuition dictate that isolated single module clusters are uncommon on good modular decompositions and so they are deprecated in the MCA approach by including the number of isolated clusters and an objective to be minimized.

The aim of the MCA measure is to capture the attributes of a good clustering. That is, it will have maximum possible cohesion (maximizing intra-edges) and minimal possible coupling (minimizing inter-edges). However, it should not put all modules into a single cluster (maximizing the number of clusters) and not produce a series of isolated clusters (so the number of isolated clusters is minimized).

Since MQ is a well-studied objective function, this is also included as an objective for MCA. This is one of the attractive aspects of a multi-objective approach; one can always include other candidate single objectives as one of the multiple objectives to be optimized. The MQ value will tend to increase if there are more clusters in the system, so it

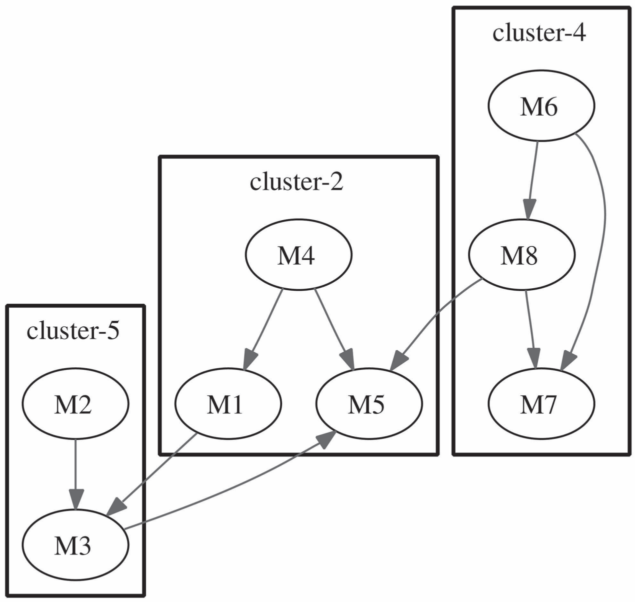

Fig. 1. The Module Dependency Graph after clustering by the two-archive algorithm.

also makes sense to include the number of clusters in the modularization as an objective. Notice that this objective is in partial conflict with the objective of minimizing the number of isolated clusters. Furthermore, the relationship between cohesion and coupling is potentially in conflict, making this a nontrivial multi-objective problem.

To illustrate the MCA approach, consider the MDG in Fig. 1. The objective values for MCA are as follows:

- intra-edges of all clusters (cohesion): 6,
- inter-edges of all clusters (coupling): -6,
- the number of clusters: 3,
- MQ: 1.928571,
- the number of isolated clusters: 0.

The sum of inter-edge of all clusters is multiplied by -2 because each edge is counted twice. The number of isolated clusters is multiplied by -1 (since it is to be minimized).

3.2 The Equal-Size Cluster Approach

The Equal-size Cluster Approach does not attempt to optimize for the number of clusters in the modularization. However, this does not mean that solutions may not emerge that happen to have a large number of clusters. Rather, the number of clusters is left as a implicit consequence of the other optimization objectives, allowing the search process the freedom to choose any number of clusters (large or small) that best suits the other explicit objectives.

However, the ECA does attempt to produce a modularization that contains clusters of roughly equal size, thereby decomposing the software system into roughly equal-size modules. This tends to mitigate against small isolated clusters and also tends to avoid the presence of one larger "god class"-like structure.

The objectives of the ECA are as follows:

- the sum of intra-edges of all clusters (maximizing),
- the sum of inter-edges of all clusters (minimizing),
- the number of clusters (maximizing),
- MQ (maximizing),
- the difference between the maximum and minimum number of modules in a cluster (minimizing).

To illustrate the ECA approach, consider again the example MDG in Fig. 1. The set of objectives for ECA are assigned as follows:

- intra-edges of all clusters (cohesion): 6,
- inter-edges of all clusters (coupling): -6,
- the number of clusters: 3,
- MQ: 1.928571,
- the difference between the maximum and minimum number of modules in a cluster: 1.

In this paper, these two formulations of the multi-objective clustering problem will be implemented in terms of the two-archive multi-objective evolutionary algorithm of Praditwong and Yao [26]. This algorithm has been applied to other multi-objective problems, but this paper is the first to report on its application to the module clustering problem.

4 Experimental Setup

This section describes the experiments conducted to compare the multi-objective and single-objective software module clustering problems.

4.1 Research Questions

1. **MQ Value as Assessment Criterion**: How well does the two-archive multi-objective search perform when compared against the Bunch approach using the MQ value as the assessment criterion?

   This question compares the two-archive approach to Bunch, using Bunch's own fitness value. It would be expected that Bunch, optimizing for the single objective of MQ, should be able to outperform the two-archive approach, which is optimizing for a balance between this and several other objectives.
2. **Cohesion and Coupling**: How well do the two-archive algorithm and the Bunch perform at optimizing each of the two primary software engineering objectives of low coupling and high cohesion?

   This research question focuses on the primary software engineering objectives of cohesion and coupling. Notwithstanding other interesting assessments, these two criteria are those for which automated software modularization was conceived, so they form a natural topic for investigation in this paper.
3. **Pareto Optimality as Assessment Criterion**: How good is the Pareto front achieved by the two approaches?

   This question compares Bunch to the two-archive approach according to the goals of the two-archive approach. It would be expected that the two-archive approach would prevail in such a comparison since it is designed to solve multi-objective problems.
4. **Location of Solutions on the Approximated Pareto Front**: What do the distributions of the sets of solutions produced by each algorithm look like?

   This question is concerned with the qualitative evaluation of the solutions produced. As a qualita-

```
Set generation number, m:= 0
Choose the initial population of candidate solutions, P(0)
Evaluate the fitness for each individual of P(0), F(P_i(0))
loop
   Recombine: P(m) := R(P(m))
   Mutate : P(m) := M(P(m))
   Evaluate: F(P(m))
   Select: P(m+1) := S(P(m))
   m := m+1
   exit when goal or stopping condition is satisfied
end loop;
```

Fig. 2. A generic genetic algorithm.

tive question, it is naturally a little more subjective than the other questions. However, it does decompose into two related subquestions, for which a quantitative analysis is possible:

a. How diverse are the solutions produced?
b. What is the relationship between the areas of the solution space covered by each approach?

5. **Effort**: What is the computational expense of executing each of the two approaches in terms of the number of fitness evaluations required.

   As well as comparing each algorithm for the number of evaluations required, we shall also give each the same budget of fitness evaluations (i.e., the same effort) and see whether one outperforms the other for quality of results, as measured by the MQ values obtained and the intra- and extra-edges present in the solutions obtained. Finally, we shall also consider the relationship between the size of the problem and the effort (measured by the number of fitness evaluations required).

4.2 Test Problems

The experiment studies the application of the algorithms to 17 different MDGs. The numbers of modules vary from 20 to over 100. The MDG in this experiment has two types. The first type is unweighted edges and the second type is weighted edges as shown in Table 2. In unweighted graphs, an edge denotes a unidirectional method or a variable passed between two modules. The weighted edge is assigned by considering the number of unidirectional method or variables passed between two modules; the greater the weight, the more dependency between two modules [18].

4.3 Genetic Algorithms

Genetic algorithms use concepts of population and of recombination inspired by Darwinian Evolution [16]. A generic genetic algorithm [6] is presented in Fig. 2.

An iterative process is executed, initialized by a randomly chosen population. The iterations are called generations and the members of the population are called chromosomes because of their analogs in natural evolution. The process terminates when a population satisfies some predetermined condition (or a certain number of generations have been exceeded).

At each iteration (that is, each generation), some members of the population are recombined, crossing over elements of their chromosomes. A fraction of the offspring of this union are mutated and, from the offspring and the original population, a selection process is used to determine the new population. Crucially, recombination and selection are guided by the fitness function, fitter chromosomes having a greater chance to be selected and recombined.

There are many variations on this overall process, but the crucial ingredients are the way in which the fitness guides the search, the recombinatory, and the population-based nature of the process. In the application of any genetic algorithm to any problem, there is a need for a tuning phase to determine the best choice of parameter values governing the likelihood of mutation, crossover, and the determination of the size of the population.

4.4 Algorithmic Parameters

The genetic encoding used here employs the same system as that introduced by Doval et al. for the Bunch system [10]. The crossover operator uses single-point crossover and the mutation operator uses single-point mutation [10].

Algorithmic parameters are dependent on the number of modules (N). The probability of crossover is 0.8 if the population size is less than 100. Otherwise, the probability is 1.0. The probability of mutation is $0.004log_2(N)$. The population size is $10N$ and the maximum number of generations is $200N$. The total size of archives is equal to the size of the population.

The hill-climbing algorithm used in the experiments reported upon here is the Bunch API [19]. The algorithm uses the hill-climbing method from the Bunch library with one individual. A first neighbor which produces a better result is accepted (this is the "first ascent" hill-climbing approach). The output files (in dot format) were generated for the detailed level; this output is the lowest level of the Bunch cluster tree and the one that tends to produce the highest value of MQ.

Higher levels than the detailed level are essentially clusters of clusters, which produce a lower value of MQ. While these metaclusters may be very useful to engineer, they are not an appropriate choice for an unbiased empirical comparison with the multi-objective approach because the multi-objective approach always produces results at the detailed level.

The other parameters are set to their default settings. The information reported, such as the number of intra-edges, the number of inter-edges, MQ, was calculated from the dot format file.

4.5 Collecting Results from Experiment

Each execution of each algorithm on each MDG was independently repeated 30 times. There are two different ways to calculate the average of the MQ. The hill-climbing algorithm gives only one solution in each run. The average of MQ can be calculated indirectly from the solutions. However, the two-archive algorithm produces the set of solutions. The solution with the highest MQ is chosen to be the best solution in each run. Thus, the average of the MQ of obtained solutions from the two-Archive algorithm is estimated using the representatives from 30 runs. This is the method to collect the MQ values from the experiment.

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TABLE 1
The Systems Studied

	Name	Modules	Links
Unweighted	mtunis	20	57
	ispell	24	103
	rcs	29	163
	bison	37	179
	grappa	86	295
	bunch	116	365
	incl	174	360
Weighted	icecast	60	650
	gnupg	88	601
	inn	90	624
	bitchx	97	1653
	xntp	111	729
	exim	118	1225
	mod_ssl	135	1095
	ncurses	138	682
	lynx	148	1745
	nmh	198	3262

Both algorithms, the hill-climbing algorithm and the two-archive algorithm, give clustered systems when they finish searching. The hill-climbing algorithm has only one system per run, while the two-Archive algorithm selects the system which corresponds the highest MQ value. The numbers of intra-edges and inter-edges are calculated by analysis of the clustered systems yielded by the algorithms.

5 Results and Analysis

This section presents the results of the empirical study. Each section addresses one of the five research questions outlined in Section 4. The results concern three algorithms, the Bunch hill-climbing algorithm, and the two multi-objective formulations of the clustering problem, ECA and MCA, described earlier in Section 3. Table 1 presents details of the subject MDGs studied. These systems are not necessarily "degraded" systems in terms of their modular structure, but they have been studied widely by other researchers to evaluate their algorithms for module clustering and so they denote reasonable choices for comparison.

5.1 The MQ Value as Assessment Criterion

This section presents the results of the experiments that compare the MQ values obtained for the three approaches. That is, the results assess how well the two multi-objective approaches perform when compared with Bunch, using Bunch's sole criterion: MQ.

Tables 2 and 3 present the results comparing MCA and ECA, respectively, with the hill-climbing approach, while Table 4 shows the comparison of results between the two multi-objective approaches (MCA and ECA). Bold numbers denote comparisons where there is a significant difference (at the 95 percent confidence level) in the means of MQ values found between the approaches (compared using a two-tailed t-test).

In Table 2, the results from two algorithms were comparable. There is good evidence to suggest that for the unweighted problems, the hill-climbing algorithm outperformed the MCA approach. That is, the hill-climbing algorithm gives higher values for MQ in six from seven problems, including four problems in which the results are

TABLE 2
Comparison of Solutions Found by the MCA Approach and Bunch's Hill-Climbing Approach Using a Two-Tailed t-Test with 58 Degrees of Freedom

	Name	MCA		Hill-Climbing		t-test
		Mean	STD	Mean	STD	
Unweighted	mtunis	2.294	0.013	2.249	0.060	0.914
	ispell	2.269	0.043	2.337	0.022	-1.461
	rcs	2.145	0.034	2.218	0.020	-1.726
	bison	2.416	0.038	2.639	0.041	**-4.331**
	grappa	11.586	0.106	12.676	0.017	**-16.977**
	bunch	12.145	0.225	13.536	0.054	**-14.420**
	incl	11.811	0.351	13.568	0.035	**-15.480**
Weighted	icecast	2.401	0.057	1.779	0.145	**7.574**
	gnupg	6.259	0.072	4.869	0.168	**15.549**
	inn	7.421	0.077	6.720	0.180	**7.571**
	bitchx	3.572	0.055	2.465	0.200	**11.988**
	xntp	6.482	0.110	6.655	0.151	-1.855
	exim	5.316	0.132	5.199	0.166	1.174
	mod_ssl	8.832	0.097	7.906	0.293	**8.129**
	ncurses	10.211	0.145	9.836	0.181	**3.602**
	lynx	3.447	0.086	3.488	0.124	-0.494
	nmh	6.671	0.177	7.012	0.254	**-2.847**

Numbers in bold are significant at the 95 percent level.

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TABLE 3
Comparison of Solutions Found by the ECA Approach and Bunch's Hill-Climbing Approach Using a Two-Tailed t-Test with 58 Degrees of Freedom

	Name	ECA		Hill-Climbing		t-test
		Mean	STD	Mean	STD	
Unweighted	mtunis	2.314	0.000	2.249	0.060	1.474
	ispell	2.339	0.022	2.337	0.022	0.042
	rcs	2.239	0.022	2.218	0.020	0.556
	bison	2.648	0.029	2.639	0.041	0.177
	grappa	12.578	0.053	12.676	0.017	-2.017
	bunch	13.455	0.088	13.536	0.054	-1.171
	incl	13.511	0.059	13.568	0.035	-1.018
Weighted	icecast	2.654	0.039	1.779	0.145	**11.158**
	gnupg	6.905	0.055	4.869	0.168	**23.663**
	inn	7.876	0.046	6.72	0.180	**13.320**
	bitchx	4.267	0.027	2.465	0.200	**20.703**
	xntp	8.168	0.076	6.655	0.151	**17.400**
	exim	6.361	0.084	5.199	0.166	**12.734**
	mod_ssl	9.749	0.071	7.906	0.293	**16.735**
	ncurses	11.297	0.133	9.836	0.181	**14.287**
	lynx	4.694	0.060	3.488	0.124	**15.410**
	nmh	8.592	0.148	7.012	0.254	**13.647**

Numbers in bold are significant at the 95 percent level.

statistically significant. However, for weighted MDG problems, the results provide evidence to suggest that the MCA approach outperforms the hill-climbing approach. That is, MCA beats the hill-climbing algorithms in 7 from 10 problems, including six in which the results are statistically significant.

This finding was something of a surprise. One would expect the hill-climbing approach to perform well at

TABLE 4
The Averaged MQ Values of the Best Solutions Found by the Two-Archive Algorithm with Maximizing Cluster Approach, and by the Two-Archive Algorithm with Equal-Size Cluster Approach, and the Value of a Two-Tailed t-Test with 58 Degrees of Freedom

	Name	ECA		MCA		t-test
		Mean	STD	Mean	STD	
Unweighted	mtunis	2.314	0.000	2.294	0.013	0.991
	ispell	2.339	0.022	2.269	0.043	1.496
	rcs	2.239	0.022	2.145	0.034	**2.176**
	bison	2.648	0.029	2.416	0.038	**4.873**
	grappa	12.578	0.053	11.586	0.106	**13.625**
	bunch	13.455	0.088	12.145	0.225	**12.830**
	incl	13.511	0.059	11.811	0.351	**14.535**
Weighted	icecast	2.654	0.039	2.401	0.057	**4.473**
	gnupg	6.905	0.055	6.259	0.072	**9.932**
	inn	7.876	0.046	7.421	0.077	**7.101**
	bitchx	4.267	0.027	3.572	0.055	**13.267**
	xntp	8.168	0.076	6.482	0.110	**21.451**
	exim	6.361	0.084	5.316	0.132	**12.321**
	mod_ssl	9.749	0.071	8.832	0.097	**12.252**
	ncurses	11.297	0.133	10.211	0.145	**11.288**
	lynx	4.694	0.060	3.447	0.086	**17.870**
	nmh	8.592	0.148	6.671	0.177	**18.476**

TABLE 5
Number of Evaluations by the Two-Archive Algorithm and Hill-Climbing

Name	Two-Archive Algorithm	Hill-Climbing	
		Mean	STD
mtunis	800000	934.367	204.558
ispell	1152000	1823.333	509.483
rcs	1682000	3291	884.664
bison	2738000	5388.267	1453.368
grappa	14792000	68429.867	27558.047
bunch	26912000	138477.767	77102.844
incl	60552000	125424.433	45517.068
icecast	7200000	17371.733	4379.106
gnupg	15488000	55475.033	17871.995
inn	16200000	96498.633	43471.544
bitchx	18818000	89179.033	34799.29
xntp	24642000	126195.533	68732.167
exim	27848000	132139.867	68820.241
mod_ssl	36450000	222008.367	112826.268
ncurses	38088000	224815.733	97552.865
lynx	43808000	126777.767	48318.278
nmh	78408000	805155.400	511547.499

optimizing for the single-objective MQ since this is its sole objective. However, there is evidence to suggest that the multi-objective MCA approach outperforms hill climbing for weighted MDGs (though not unweighted MDGs).

Turning to the results for the ECA multi-objective approach, the surprise was even greater. There is no evidence to suggest that the ECA approach is outperformed by the hill-climbing approach for unweighted graphs. However, there is very strong evidence to suggest that the ECA approach outperforms the hill climber for weighted MDGs. That is, in no unweighted case did either approach outperform the other with statistical significance. However, for weighted

TABLE 6
Number of Evaluations by the Two-Archive Algorithm and Hill Climbing

Name	Hill-Climbing		Two-Archive Algorithm
	No. of Runs	No. of Evaluations	No. of Evaluations
mtunis	26014	24000943	24000000
ispell	19340	34560557	34560000
rcs	15363	50461933	50460000
bison	15408	82140104	82140000
grappa	5817	443791973	443760000
bunch	6346	807430167	807360000
incl	12748	1816661431	1816560000
icecast	12429	216006356	216000000
gnupg	9083	464654717	464640000
inn	5434	486010358	486000000
bitchx	7264	564579101	564540000
xntp	6162	739300758	739260000
exim	6647	835468260	835440000
mod_ssl	4755	1093626809	1093500000
ncurses	4965	1143087432	1142640000
lynx	9778	1314294774	1314240000
nmh	3107	2353426942	2352240000

TABLE 7
The Averaged MQ Values of the Best Solutions Found by the Two-Archive Algorithm with the Equal-Size Cluster Approach, and by Hill Climbing

	Name	ECA		Hill-Climbing		T-test:
		Mean	STD	Mean	STD	ECA-HC
Not weighted	mtunis	2.314	0	2.242	0.063	**6.322**
	ispell	2.339	0.022	2.334	0.024	0.970
	rcs	2.239	0.022	2.220	0.022	**4.655**
	bison	2.648	0.029	2.637	0.038	1.447
	grappa	12.578	0.053	12.677	0.019	**-28.480**
	bunch	13.455	0.088	13.537	0.055	**-8.000**
	incl	13.511	0.059	13.572	0.037	**-9.107**
Weighted	icecast	2.654	0.039	1.846	0.127	**34.760**
	gnupg	6.905	0.055	4.946	0.183	**58.528**
	inn	7.876	0.046	6.676	0.188	**34.893**
	bitchx	4.267	0.027	2.444	0.209	**47.799**
	xntp	8.168	0.076	6.636	0.125	**66.857**
	exim	6.361	0.084	5.207	0.172	**36.816**
	mod_ssl	9.749	0.071	7.934	0.306	**32.523**
	ncurses	11.297	0.133	9.804	0.182	**44.951**
	lynx	4.694	0.060	3.489	0.131	**50.470**
	nmh	8.592	0.148	7.062	0.265	**31.517**

graphs, the ECA approach outperforms the hill climber in all problems studied with statistically significant differences in the means in all cases, as indicated in Tables 7 and 8.

This set of comparisons of the two multi-objective approaches with the single-objective hill climber provides evidence to suggest that both multi-objective algorithms can outperform the single-objective hill climber when compared using the hill climber's own sole objective. The results also indicate that, of the two multi-objective approaches, ECA is to be preferred over MCA. This is borne out by the comparison of the ECA and MCA approaches (presented in Fig. 4). In all cases, the ECA approach outperforms the MCA approach and, in all but the smallest two, the results are statistically significant.

To answer Research Question 1, the results of the study provide evidence to support the claim that the Bunch hill-climbing approach produces superior MQ values for unweighted graphs than the MCA approach. However, for weighted graphs, there is a strong evidence (from the results in Tables 2 and 3) to suggest that the multi-objective research (and, in particular, the ECA version of the multi-objective search) can produce significantly better results for MQ values

TABLE 8
The Average of the Intra-Edges and the Inter-Edges of the Best Solutions Found by the Two-Archive Algorithm with the Equal-Size Cluster Approach, and by Hill Climbing

Name	ECA				Hill-Climbing				T-test:	T-test:
	Intra-edges		Inter-edges		Intra-edges		Inter-edges		Intra-edges	Inter-edges
	Mean	STD	Mean	STD	Mean	STD	Mean	STD	ECA-HC	ECA-HC
Not weighted										
mtunis	27	0	-60	0	22.643	3.489	-69.724	6.914	**6.839**	**7.702**
spell	30.033	2.798	-145.933	5.595	25.356	3.030	-156.299	5.984	**8.449**	**9.481**
rcs	47.567	7.859	-230.867	15.719	36.810	6.742	-253.372	13.446	**8.727**	**9.156**
bison	52.800	6.217	-252.400	12.434	40.225	5.944	-278.546	11.855	**11.576**	**12.067**
grappa	101.167	8.301	-387.667	16.601	82.167	3.175	-426.675	6.277	**32.230**	**33.457**
bunch	111.700	5.305	-504.600	10.611	100.632	5.707	-527.740	11.341	**10.601**	**11.153**
incl	140.200	3.836	-439.600	7.673	140.510	9.862	-439.992	19.710	-0.172	0.109
Weighted										
icecast	1643.167	208.189	-7569.667	416.378	780.828	227.609	-9295.350	455.216	**20.730**	**20.743**
gnupg	1494.167	103.830	-4413.667	207.660	905.158	129.182	-5592.698	258.341	**24.946**	**24.970**
inn	1336.900	190.263	-5046.200	380.526	519.048	122.170	-6682.903	244.343	**36.428**	**36.450**
bitchx	7840.600	633.068	-35546.800	1266.136	3050.028	939.989	-45128.934	1879.96	**27.887**	**27.890**
xntp	1117.967	54.502	-3692.067	109.004	419.447	77.202	-5090.102	154.394	**49.495**	**49.534**
exim	3146.567	525.155	-12612.867	1050.310	1029.345	292.284	-16848.317	584.563	**39.396**	**39.406**
mod_ssl	3476.800	244.174	-11008.400	488.348	1075.909	151.961	-15811.176	303.928	**85.855**	**85.870**
ncurses	806.3670	57.515	-2607.267	115.030	367.182	25.005	-3486.637	49.995	**94.738**	**94.875**
lynx	3730.633	478.016	-20546.733	956.032	1561.995	263.208	-24885.012	526.420	**44.907**	**44.917**
nmh	2704.600	236.782	-18576.800	473.564	1164.043	215.020	-21658.899	430.016	**39.016**	**39.031**

TABLE 9
The Relationship between Size and ECA Computation Time

Problem	Nodes	Time (Sec.)	
		Mean	STD
mtunis	20	8.1	0.711967
ispell	24	23.433333	0.773854
rcs	29	24	1.144703
bison	37	68.533333	10.852406
grappa	86	697.7	166.593279
bunch	116	1868.533333	409.992324
incl	174	6652.4	2006.30093
icecast	60	349.266667	29.657741
gnupg	88	2900.766667	953.430564
inn	90	1111.766667	265.050637
bitchx	97	1375.2	116.074411
xntp	111	3434.4	1005.104613
exim	118	3631.966667	949.306007
mod_ssl	135	4219.6	740.464793
ncurses	138	12298.46667	3617.612308
lynx	148	5790.366667	1693.144972
nmh	198	14021.46667	2114.663595

of weighted MDGs compared to the Bunch Hill-Climbing approach. There is also very strong evidence to suggest that the ECA approach is superior to the MCA approach in terms of MQ values obtained. The computation time of ECA was also studied and is shown in Table 9 and Fig. 3.

One of the primary reasons for such good results is that the multi-objective algorithm always searches for a non-dominated set, rather than any single solution. The diversity among the solutions in the set is explicitly encouraged by the algorithm. As a result, the multi-objective algorithm is more likely to explore widely in the search landscape. The more complex the search landscape, the more likely the multi-objective algorithm performs better. This also explains why our algorithm outperformed the single-objective method more on weighted graphs.

It is interesting to speculate as to why the ECA approach should appear to outperform the MCA approach. Clearly, more experiments and further study would be required to provide a conclusive answer to this subsidiary question. However, since the difference rests upon the way in which ECA seeks to normalize cluster size, favoring solutions that minimize the difference between cluster sizes, it must be assumed that in software systems this is a helpful guide to modularization. By contrast, seeking to punish a solution for containing isolated clusters (the MCA approach) is less helpful. In order to explore this further, experiments would be required that compared software MDGs to dependence from other (nonsoftware) sources. It may turn out that such studies could help to explain what it is that makes a dependence graph a *software dependence* graph rather than a graph in general.

5.2 Cohesion and Coupling as Assessment Criteria

This section considers the answer to the second research question, which addresses the central role played by cohesion and coupling in all work on module clustering. That is, which approach can produce the highest cohesion and the lowest

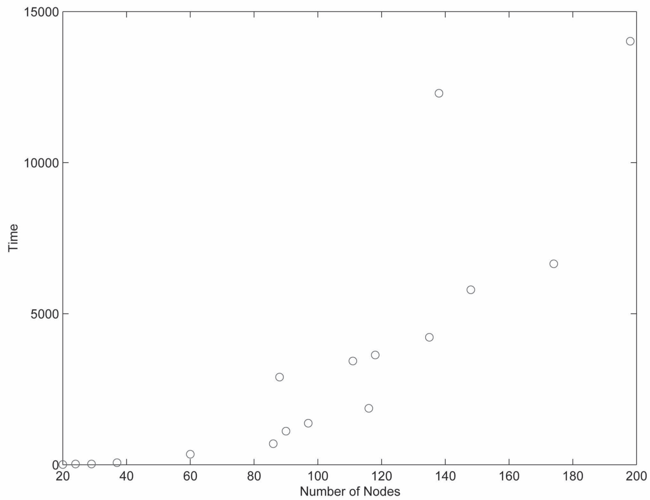

Fig. 3. The number of nodes and computation time by ECA.

coupling? Cohesion is a measure of the number of intra-edges in the modularization (those edges that lie inside a cluster), while coupling is measured by the number of inter-edges in the modularization (the edges that connect two clusters). Both of these objectives are construed as maximization problems in the formulation, so the number of inter-edges is represented by the negative of the interedges; the goal is to maximize this value (i.e., to reduce coupling).

Tables 10, 11, and 12 present the results comparing the performance of {MCA, Hill Climbing}, {ECA, Hill Climbing}, and {MCA, ECA}, respectively.

In Table 10, the comparison of MCA and Hill climbing is somewhat inconclusive for unweighted graphs, with each approach able to statistically significantly outperform the other in some cases. However, for weighted MDGs, the MCA approach outperforms the Hill-climbing approach in all cases with statistical significance.

In Table 11, the results provide strong evidence to suggest that the ECA approach outperforms the hill-climbing approach for both weighted and unweighted graphs. That is, in all but one of the problems studied, the ECA approach outperforms the hill-climbing approach with statistical significance.

Table 12 provides evidence to suggest that the ECA approach is preferable to the MCA approach; ECA statistically significantly outperforms MCA in all but one case. However, it is interesting to note that, in the one case where MCA outperforms ECA, it also does so with statistical significance. This indicates that there remains some residual merit in the MCA approach. This issue of complementarity of approaches is revisited in Section 5.4.

To answer Research Question 2, there is strong evidence (from Tables 10 and 11) to support the claim that the multi-objective approach (both the MCA and ECA versions) outperform the Hill-Climbing approach in producing solution clusterings with both higher cohesion and lower coupling for weighted graphs. Furthermore, there is also strong evidence (from Table 11) that the ECA multi-objective approach can outperform the Bunch Hill-Climbing approach on both weighted and unweighted graphs when aiming to produce solutions that minimize coupling while maximizing cohesion. This provides strong empirical evidence to support the claim that the multi-objective

TABLE 10
The Average of the Intra-Edges and the Inter-Edges of the Best Solutions Found by the Two-Archive Algorithm with Maximizing Cluster Approach, and by Hill Climbing and the Value of a Two-Tailed t-Test with 58 Degrees of Freedom

Name	MCA				Hill-climbing				T-test:	T-test:
	Intra-edges		Inter-edges		Intra-edges		Inter-edges		Intra-edges	Inter-edges
	Mean	STD	Mean	STD	Mean	STD	Mean	STD		
Unweighted										
mtunis	24.633	2.092	-64.733	4.185	22.600	3.379	-68.800	6.759	**4.761**	**6.733**
ispell	23.100	3.220	-159.800	6.440	25.833	3.761	-154.333	7.522	**-5.666**	**-8.013**
rcs	45.133	15.335	-235.733	30.669	35.033	5.822	-255.933	11.644	**12.027**	**17.009**
bison	40.367	8.231	-277.267	16.463	40.600	6.683	-276.800	13.366	-0.331	-0.468
grappa	84.767	11.190	-420.467	22.380	81.900	2.928	-426.200	5.857	**4.179**	**5.910**
bunch	73.567	8.324	-580.867	16.648	100.867	4.883	-526.267	9.766	**-41.145**	**-58.188**
incl	91.767	14.024	-536.467	28.048	140.967	11.758	-438.067	23.515	**-53.073**	**-75.056**
Weighted										
icecast	1609.900	294.921	-7636.200	589.843	733.467	238.111	-9389.070	476.222	**207.923**	**294.048**
gnupg	1104.733	167.834	-5192.530	335.669	887.200	150.659	-5627.600	301.318	**66.763**	**94.417**
inn	771.633	162.630	-6176.730	325.260	554.233	158.848	-6611.530	317.696	**66.412**	**93.920**
bitchx	7644.633	2703.349	-35938.700	5406.697	3166.267	861.843	-44895.500	1723.685	**410.808**	**580.970**
xntp	733.800	109.722	-4460.400	219.445	447.033	99.724	-5033.930	199.448	**108.531**	**153.486**
exim	3279.300	563.781	-12347.400	1127.563	1004.267	342.379	-16897.500	684.758	**413.948**	**585.411**
mod_ssl	2911.733	310.981	-12138.500	621.962	1101.633	144.082	-15758.700	288.165	**464.758**	**657.268**
ncurses	574.433	94.392	-3071.130	188.785	368.700	22.927	-3482.600	45.855	**104.035**	**147.128**
lynx	2428.567	863.007	-23150.900	1726.014	1567.800	268.807	-24872.400	537.614	**140.139**	**198.186**
nmh	2032.267	438.220	-19921.500	876.440	1120.233	213.024	-21745.500	426.048	**195.749**	**276.831**

Numbers in bold are significant at the 95 percent level.

approach is worthy of further consideration as an optimally performing approach to module clustering.

5.3 Pareto Optimality as Assessment Criterion

This section compares the multi-objective formulations with the single-objective formulation in terms of how well each performs at producing good approximations to the Pareto front. Here, the multi-objective formulations can be expected to outperform the single-objective formulation since they are designed to produce good approximations to the Pareto front, whereas the single-objective approach is not. Therefore, the more interesting part of this research question is which of the two multi-objective formulations performs best.

Tables 13, 14, and 15 display the dominance relationship for the results obtained from all three approaches. This

TABLE 11
The Average of the Intra-Edges and the Inter-Edges of the Best Solutions Found by the Two-Archive Algorithm with Equal-Size Cluster Approach, and by Hill Climbing and the Value of a Two-Tailed t-Test with 58 Degrees of Freedom

Name	ECA				Hill-climbing				T-test:	T-test:
	Intra-edges		Inter-edges		Intra-edges		Inter-edges		Intra-edges	Inter-edges
	Mean	STD	Mean	STD	Mean	STD	Mean	STD		
Unweighted										
mtunis	27.000	0.000	-60.000	0.000	22.600	3.379	-68.800	6.759	**13.110**	**18.540**
ispell	30.033	2.798	-145.933	5.595	25.833	3.761	-154.333	7.522	**8.983**	**12.704**
rcs	47.567	7.859	-230.867	15.719	35.033	5.822	-255.933	11.644	**18.559**	**26.247**
bison	52.800	6.217	-252.400	12.434	40.600	6.683	-276.800	13.366	**18.605**	**26.311**
grappa	101.167	8.301	-387.667	16.601	81.900	2.928	-426.200	5.857	**31.491**	**44.536**
bunch	111.700	5.305	-504.600	10.611	100.867	4.883	-526.267	9.766	**18.590**	**26.290**
incl	140.200	3.836	-439.600	7.673	140.967	11.758	-438.067	23.515	-1.063	-1.504
Weighted										
icecast	1643.167	208.189	-7569.670	416.378	733.467	238.111	-9389.070	476.222	**235.855**	**333.550**
gnupg	1494.167	103.830	-4413.670	207.660	887.200	150.659	-5627.600	301.318	**208.397**	**294.718**
inn	1336.900	190.263	-5046.200	380.526	554.233	158.848	-6611.530	317.696	**229.433**	**324.467**
bitchx	7840.600	633.068	-35546.800	1266.136	3166.267	861.843	-44895.500	1723.685	**662.175**	**936.457**
xntp	1117.967	54.502	-3692.070	109.004	447.033	99.724	-5033.930	199.448	**295.911**	**418.482**
exim	3146.567	525.155	-12612.900	1050.310	1004.267	342.379	-16897.500	684.758	**398.380**	**563.395**
mod_ssl	3476.800	244.174	-11008.400	488.348	1101.633	144.082	-15758.700	288.165	**660.230**	**933.706**
ncurses	806.367	57.515	-2607.270	115.030	368.700	22.927	-3482.600	45.855	**267.277**	**377.987**
lynx	3730.633	478.016	-20546.700	956.032	1567.800	268.807	-24872.400	537.614	**433.486**	**613.041**
nmh	2704.600	236.782	-18576.800	473.564	1120.233	213.024	-21745.500	426.048	**409.170**	**578.654**

Numbers in bold are significant at the 95 percent level.

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

TABLE 12
The Average of the Intra-Edges and the Inter-Edges of the Best Solutions Found by the Two-Archive Algorithm with Equal-Size Cluster Approach, and by the Two-Archive Algorithm with Maximizing Cluster Approach, and the Value of a Two-Tailed t-Test with 58 Degrees of Freedom

Name	ECA				MCA				T-test:	T-test:
	Intra-edges		Inter-edges		Intra-edges		Inter-edges		Intra-edges	Inter-edges
	Mean	STD	Mean	STD	Mean	STD	Mean	STD		
Unweighted										
mtunis	27.000	0.000	-60.000	0.000	24.633	2.092	-64.733	4.185	**8.961**	**12.673**
ispell	30.033	2.798	-145.933	5.595	23.100	3.220	-159.800	6.440	**15.481**	**21.893**
rcs	47.567	7.859	-230.867	15.719	45.133	15.335	-235.733	30.669	**2.767**	**3.914**
bison	52.800	6.217	-252.400	12.434	40.367	8.231	-277.267	16.463	**17.916**	**25.337**
grappa	101.167	8.301	-387.667	16.601	84.767	11.190	-420.467	22.380	**20.346**	**28.774**
bunch	111.700	5.305	-504.600	10.611	73.567	8.324	-580.867	16.648	**56.575**	**80.009**
incl	140.200	3.836	-439.600	7.673	91.767	14.024	-536.467	28.048	**62.772**	**88.772**
Weighted										
icecast	1643.167	208.189	-7569.670	416.378	1609.900	294.921	-7636.200	589.843	**8.123**	**11.488**
gnupg	1494.167	103.830	-4413.670	207.660	1104.733	167.834	-5192.530	335.669	**129.413**	**183.017**
inn	1336.900	190.263	-5046.200	380.526	771.633	162.630	-6176.730	325.260	**164.813**	**233.081**
bitchx	7840.600	633.068	-35546.800	1266.136	7644.633	2703.349	-35938.700	5406.697	**18.582**	**26.280**
xntp	1117.967	54.502	-3692.070	109.004	733.800	109.722	-4460.400	219.445	**164.196**	**232.208**
exim	3146.567	525.155	-12612.900	1050.310	3279.300	563.781	-12347.400	1127.563	**-22.031**	**-31.157**
mod_ssl	3476.800	244.174	-11008.400	488.348	2911.733	310.981	-12138.500	621.962	**131.357**	**185.767**
ncurses	806.367	57.515	-2607.270	115.030	574.433	94.392	-3071.130	188.785	**103.071**	**145.764**
lynx	3730.633	478.016	-20546.700	956.032	2428.567	863.007	-23150.900	1726.014	**194.749**	**275.417**
nmh	2704.600	236.782	-18576.800	473.564	2032.267	438.220	-19921.500	876.440	**141.740**	**200.451**

Numbers in bold are significant at the 95 percent level.

dominance relationship is used to compare any two solutions in multi-objective space.

The three software engineering objectives considered are the intra-edge and the inter-edge measurement, and, for backward compatibility with work on single-objective formulations, the MQ value obtained. These objectives can be thought of as collectively denoting the quality of the clustering produced.

In these tables, A denotes the hill-climbing algorithm, B denotes the MCA, and C denotes the ECA. The heading N_{XY} denotes the number of solutions generated by X that are dominated by solution in Y. In comparison, X is better than Y if N_{XY} is small and N_{YX} is large.

TABLE 13
Results of Dominated Comparison

	Name	N_{AB}	N_{BA}
Unweighted	mtunis	23	19
	ispell	7	30
	rcs	2	21
	bison	0	29
	grappa	0	23
	bunch	0	30
	incl	0	30
Weighted	icecast	30	0
	gnupg	30	0
	inn	30	0
	bitchx	30	0
	xntp	23	10
	exim	30	0
	mod_ssl	30	0
	ncurses	30	0
	lynx	26	12
	nmh	13	1

A: the hill-climbing algorithm and B: the Two-Archive algorithm with the maximizing cluster approach.

TABLE 14
Results of Dominated Comparison

	Name	N_{AC}	N_{CA}
Unweighted	mtunis	23	0
	ispell	24	13
	rcs	30	3
	bison	28	17
	grappa	27	0
	bunch	16	11
	incl	22	27
Weighted	icecast	30	0
	gnupg	30	0
	inn	30	0
	bitchx	30	0
	xntp	30	0
	exim	30	0
	mod_ssl	30	0
	ncurses	30	0
	lynx	30	0
	nmh	30	0

A: the hill-climbing algorithm and C: the Two-Archive algorithm with the equal-size cluster approach.

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TABLE 15
Results of Dominated Comparison

	Name	N_{BC}	N_{CB}
Unweighted	mtunis	19	0
	ispell	30	0
	rcs	27	0
	bison	30	0
	grappa	30	0
	bunch	30	0
	incl	30	0
Weighted	icecast	29	0
	gnupg	30	0
	inn	30	0
	bitchx	24	0
	xntp	30	0
	exim	30	0
	mod_ssl	30	0
	ncurses	30	0
	lynx	30	0
	nmh	29	0

B: the Two-Archive algorithm with the maximizing cluster approach and C: the Two-Archive algorithm with the equal-size cluster approach.

Table 13 shows that the number of solutions produced by hill climbing outperforms MCA for unweighted problems (six from seven problems), while, in weighted systems, the MCA outperforms the hill-climbing algorithm in all problems. This indicates that hill climbing is effective, perhaps surprisingly so, for unweighted MDGs.

Table 14 provides strong evidence that ECA outperforms hill climbing for both weighted and unweighted MDGs. That is, the values of N_{AC} are higher than N_{CA} in 16 of 17 of the solutions.

These two findings taken together indicate the ECA is better than hill climbing, while MCA is only better than hill climbing for weighted graphs, leading to suspicion that ECA outperforms MCA. This suspicion is confirmed by the results from Table 15, which compares ECA and MCA. This table shows that ECA comfortably outperforms MCA in all of the problems studied.

To answer Research Question 3, as expected the single-objective formulation implemented by Bunch is not well suited to finding nondominated solutions for a set of objectives. The results are particularly compelling for the ECA multi-objective approach, which comfortably outperforms the other approaches.

5.4 Location of Solutions

This section considers the location of solutions produced by the two approaches. In order to examine the location of solutions, it is convenient to compare two of the primary software engineering objectives. For this reason, cohesion (intra-edges) and the MQ value are chosen to see the trade-off between these two objectives. The previous sets of experiments have indicated a strong degree of difference between the results of weighted and unweighted MDGs. Therefore, in considering location of solutions, the results are categorized into those for weighted MDGs and those for unweighted MDGs. Fig. 4 shows the locations of solutions in this two-objective space for unweighted MDGs, while Fig. 5 shows the location for unweighted MDGs.

In all figures, the two objectives are to be maximized, so the optimal solutions are located in the uppermost and rightmost areas of the two-objective space, while the least optimal are located in the lowermost and leftmost areas of the space. The results in Fig. 4 confirm the earlier findings that ECA is to be preferred over MCA for unweighted MDGs and also that hill climbing (labeled HC) is a strong performer on unweighted graphs. The results in Fig. 5 are perhaps a little more interesting. They reveal that each of the three algorithms concentrates in a different region of the two objective search space. Visually, it is apparent that the hill-climbing approach tends to concentrate on the less optimal areas of the space, while both ECA and MCA are focused on more productive locations. However, of ECA and MCA, it is not always possible to say that ECA is the better of the two. This suggests that for optimal results, both ECA and MCA should be used. Although previous studies indicate that ECA will tend to outperform MCA, the visualization of result locations in two-dimensional objective space indicates that the two approaches concentrate on different areas of the solution space and that MCA is occasionally able to produce results that outperform ECA for one of the two objectives.

To answer Research Question 4, the resulting locations indicate that the three approaches produce solutions in different parts of the solution space. This indicates that no one solution should be preferred over the others for a complete explanation of the module clustering problem. While the results for the ECA multi-objective approach indicate that it performs very well in terms of MQ value, nondominated solutions, and cohesion and coupling, this does not mean that the other two approaches are not worthy of consideration, because the results suggest that they search different areas of the solution space.

It is interesting to note how the different approaches produce solutions in different regions of the solution space according to the fitness function values obtained. This suggests that each technique also finds different remodularizations of the software, though more work is required to examine this in more detail.

5.5 Computational Effort

This section compares the effort required to solve the clustering problem using the traditional hill-climbing approach and the new multi-objective approaches introduced in this paper. The results indicate that there is a trade-off between effort and quality of results. That is, the number of evaluations required to achieve the better results of the multi-objective approach is two orders of magnitude greater than that required for the hill climber. However, even if we allow the Hill Climber the same number of fitness evaluations as the multi-objective approaches, the results for the multi-objective approach are still typically better than those obtained by the Hill Climber. Finally, we explore the relationship between the size of the problem and the number of fitness evaluations required by the multi-objective approach. This study indicates that there is no obvious relationship between size of problem and effort.

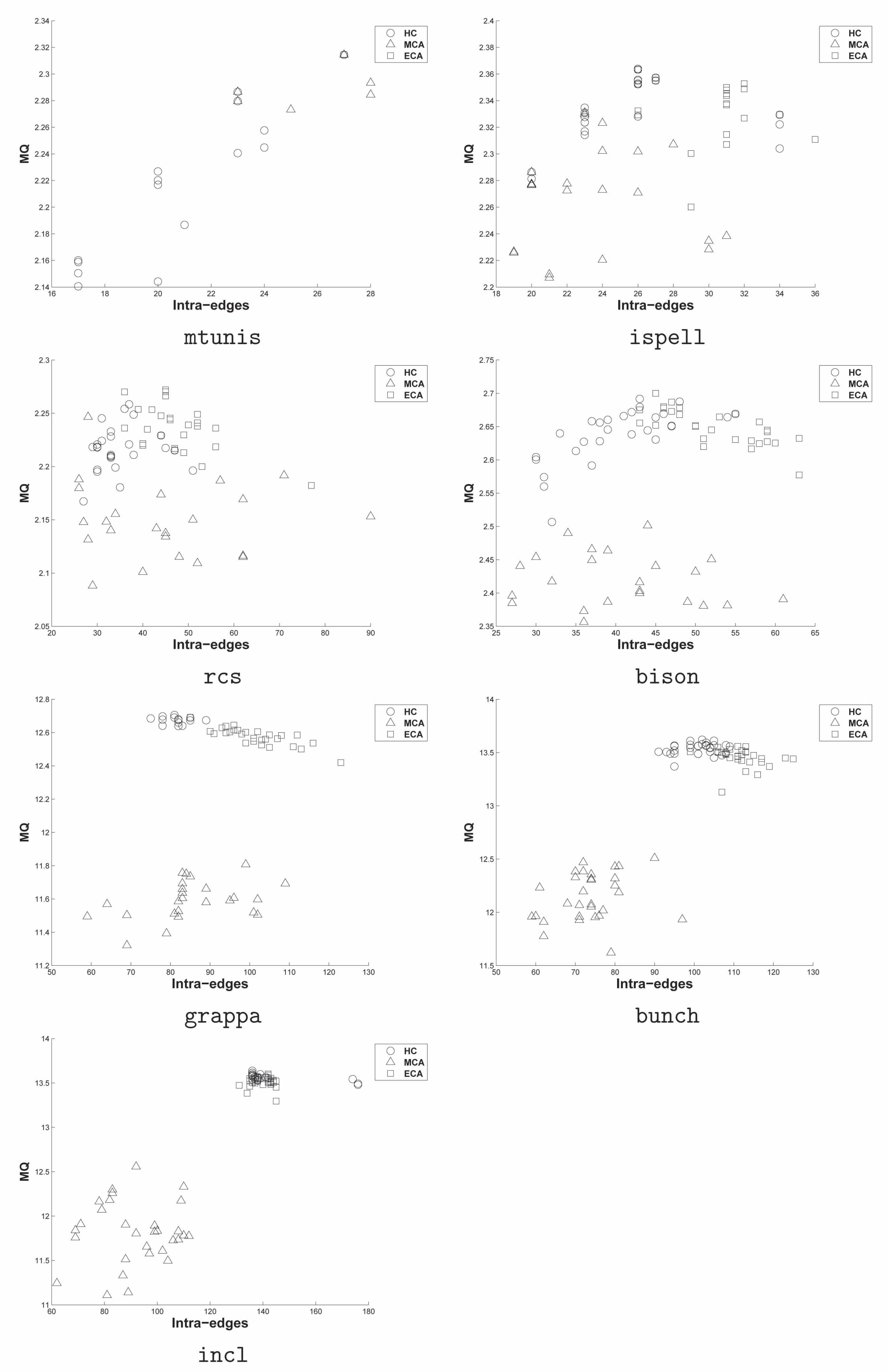

Fig. 4. Solutions in the intra-edge and MQ space for unweighted MDGs.

5.5.1 *Number of Evaluations*

An important factor for search algorithms is a number of evaluations. The number of evaluations indicates the computational cost of an algorithm. The numbers of evaluations of all algorithms are shown in Table 5. The two approaches (MCA and ECA) that use the two-archive algorithm use the same number of fixed evaluations. The hill-climbing algorithm will terminate when it can no longer find a neighbor that produces the better MQ. Thus, the numbers of evaluations for the hill-climbing algorithm are

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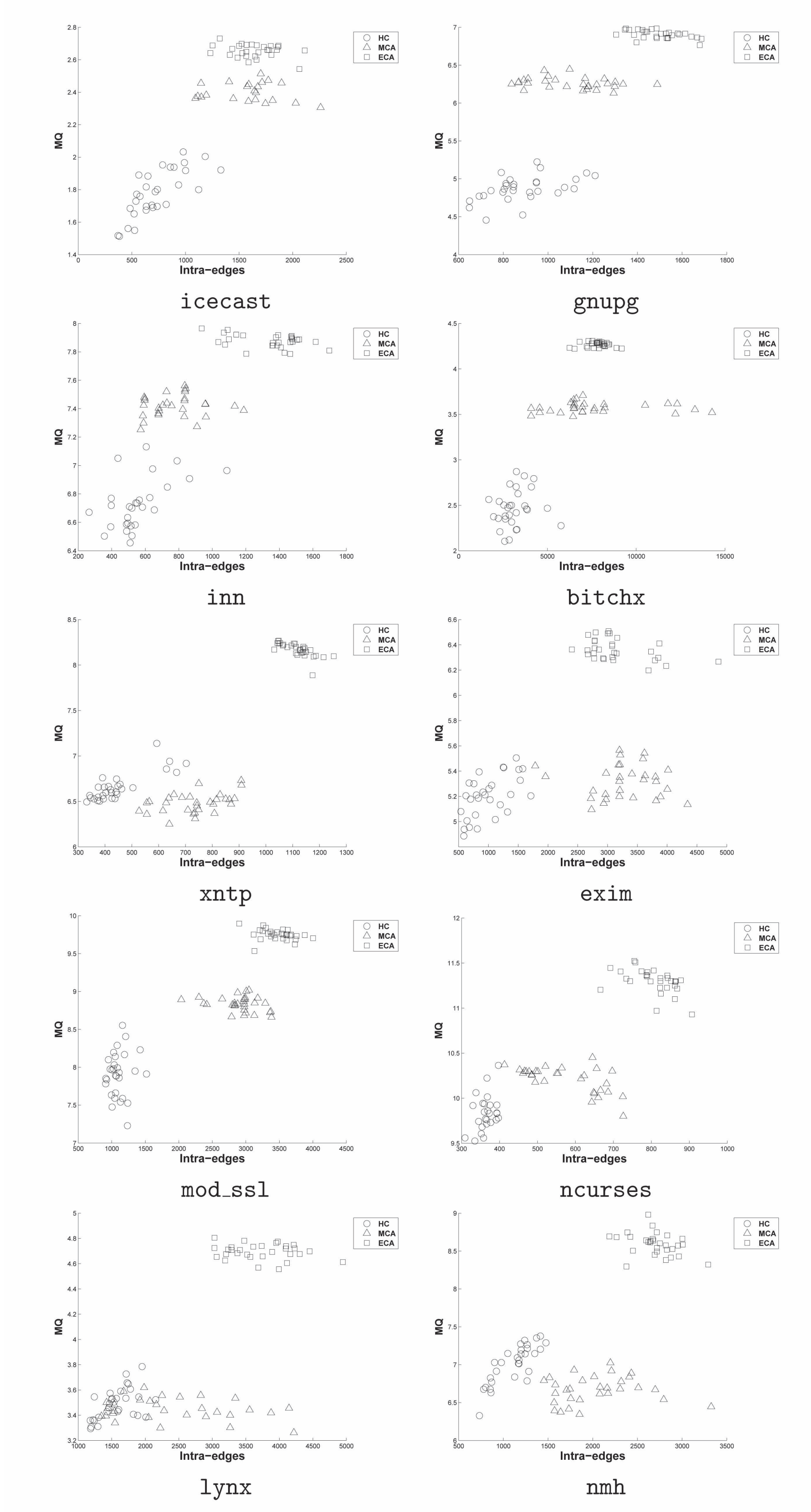

Fig. 5. Solutions in the intra-edge and MQ space for weighted MDGs.

not fixed. The numbers of evaluations in this table are averaged values from 30 independent runs.

To answer Research Question 5, the results clearly demonstrate the additional cost incurred by a multi-objective search using a genetic algorithms. The Bunch hill-climbing

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approach is at least two orders of magnitude more time-efficient when compared to the two-archive Pareto genetic algorithm. This confirms the widely observed principle that hill climbing is a fast and simple search technique when compared to the genetic algorithm approach. This is particularly true in cases where multiple objectives have to be satisfied using Pareto optimality because of the additional overheads that accrue from the maintenance of a nondominating set that approximates the Pareto front.

Whether the additional cost is justified by the superior results will depend upon the application domain. In many cases, remodularization is an activity that is performed occasionally and for which the software engineer may be prepared to wait a few minutes (even hours) for results if this additional waiting time produces significantly better results. Specifically, it is likely that the software engineer will be prepared to wait for results in several situations. For example, where a system has become difficult to maintain through degradation of structure, the engineer may be prepared to wait even for several days in order to obtain an assessment of the optimally improved structure.

Module clustering represents the top level structure of the system. As such, it is unlikely that the entire structure of a system will undergo a major overhaul on a regular basis. When such an overhaul is required, it is likely to be a significant event and so it will be important to obtain the best possible results. For these best possible results, it is quite likely that the engineer will be prepared to wait. However, in other more speculative situations, where the engineer asks a "what if?" question, then it may be more attractive to obtain results that are merely fast and "good enough." In these cases, the single-objective approach may remain an attractive alternative.

5.5.2 Head To Head Comparison

In this experiment, we give the Hill Climber the same number of evaluations as the multi-objective approach to determine whether it can produce equally good or better solutions when allowed the same budget of fitness evaluations (i.e., the same effort). The Hill Climber is simply restarted each time it reaches the summit of a hill at a random point and allowed to continue with random restarts until it exhausts the budget of fitness evaluations. This is known as "Random Restart Hill Climbing."

Table 5 shows the number of evaluations used by the ECA two-archive approach. We have given the Hill Climber the same number of evaluations as used in all 30 runs of the ECA algorithm for complete fairness. That is, for example, considering the mtunis problem, the number of evaluations of ECA is 800,000 and it is repeated 30 times (to allow for a meaningful statistical comparison of results earlier in the paper). Thus, the total number of evaluations is 24,000,000. The Hill-Climbing approach was performed until the number of evaluations passes 24,000,000. The number might slightly exceed this "fitness evaluation budget" because the current hill climb is allowed to complete before the budget is checked. This ensures that the Hill Climber is afforded at least the same number of evaluations as the ECA approach. Table 6 shows the number of evaluations and the number of runs performed by the Hill-Climbing approach.

Table 7 presents the MQ value obtained for each algorithm. Hill Climbing cannot find better solutions in terms of MQ when the number of evaluations allowed is increased to the total used by the multi-objective approach. For only three of the problems, *grappa*, *bunch*, and *incl*, does the MQ obtained by Hill Climbing outperform that found by the ECA algorithm. In the other problems, the ECA algorithm finds better MQ values than the Hill-Climbing algorithm.

A comparison of intra-edge and inter-edge is shown in Table 8. Hill Climbing can find the solutions with good intra-edge and inter-edge, but it does not outperform ECA for result quality when it has the same number of evaluations.

5.6 Exploration of the Relationship between Problem Size and Number of Fitness Evaluations Required

In this section, we consider the relationship between the size of the problem and the number of fitness evaluations required. The results show that there is no apparent relationship between the two. That is, there is no strong correlation between the sizes of systems (listed in Table 1) and the effort expended by the search techniques (listed in Tables 5 and 6).

This provides some tentative evidence to suggest that the difficulty of a problem (for the multi-objective approach) is not a function of the problem's size; the complexity of the problem may not be directly related to its size. However, as one might expect, the larger systems do seem to take more fitness evaluations. More work is required with more systems in order to fully determine whether there is any relationship between the size of the MDG and the number of fitness evaluations required.

It may be that search problem difficulty is related to problem complexity, not problem size, and that, should there turn out to be some correlation, then the difficulty of the search might act as some form of guide as to the complexity of the problem. However, this remains purely speculation at this point.

6 Use of Automated and Semi-Automated Modularization-Based Cohesion and Coupling

Automated approaches to modularization such as that presented in this paper focus on automated algorithms that seek out new partitions of software, maximizing cohesion and minimizing coupling. There have been empirical studies that show that low coupling and high cohesion are desirable because they tend to be correlated with a lower propensity to contain faults [4]. However, care is required in extrapolating from these studies to the work reported here; it cannot be assumed that automated remodularization will necessarily improve quality attributes such as fault proneness.

Also, it would be wrong to assume that cohesion and coupling are the only requirements for software module quality. Many other factors have to be taken into account when deciding upon the quality of software and no attempt is made in this paper to claim that automatically remodularized software will necessarily be less fault prone nor to suggest that it will have other desirable properties.

Finally, though the approach advocated here is automated, this does not mean that a practicing software engineer should simply press a "modularize button" and accept the results of automated modularization without question. Rather, tools that use these automated techniques are more likely to be interactive; the tool merely suggesting candidates for remodularization, perhaps indicating functions that could be moved to improve measurements of cohesion and coupling. The user of such a tool would then consider these suggestions and decide whether or not to accept them.

This paper adds to the previous work on cohesion and coupling by providing automated techniques that can be used to make such suggestions. It improves the measurements of cohesion and coupling that can be achieved so that, where this is desirable, the user will have potentially more interesting suggestions from the tool to consider.

A further interesting practical contribution of this work is the way in which the paper indicates that multi-objective search techniques can be useful for improving the fitness scores obtained for single-objective problems. This is a phenomenon observed in the wider optimization community [5], but, to the authors' knowledge, it is the first time that this phenomenon has been demonstrated in search-based software engineering problems.

That is, the search for solutions that maximize the widely studied MQ measurement can be improved by searching for solutions that solve this and several other objectives, as the results in the present paper indicate. This finding seems surprising at first glance; how can adding objectives make a problem easier to solve? The resolution of this apparent paradox is to be found in the way in which the other objectives contribute guidance to the solution of the primary objective (in this case MQ). This finding may be useful for other SBSE problems; it may be that even essentially single-objective SBSE problems can be reformulated as multiple-objective search problems in which the additional objectives provide guidance to the solution of the primary objective and a Pareto optimal search can thereby find superior solutions that achieve higher scores for the primary objective.

The application of search-based modularization is not merely a technique for application to systems that have become degraded through ad hoc maintenance, though it may be particularly useful for such systems. Like all tools to support software engineers in their decision making, the approach can be used to raise questions about modularization choices, even for very well-maintained systems. Where the search-based approach suggests a remodularization that will produce a noticeable improvement in cohesion and coupling, this can be a starting point for investigation, even for well-behaved systems.

Furthermore, where the automated approach produces a suggestion that is not followed, this may indicate a situation where there are hidden dependencies not reflected in the MDG. These dependencies will be hidden to the automated tool, but may be known to the engineer. They may cause the engineer to reject the modularization suggestions. In such cases, the tool may have flagged up a need for additional design documentation to record and document such dependencies. The authors' experience with code level dependencies from industrial partners indicates that real code does contain many such hidden dependencies.

7 Threats to Validity

For an experiment not involving human subjects, there are two potential threats to validity that need to be considered. These are threats to external validity and internal validity. External validity (or selection validity) concerns the degree to which the findings can be generalized to the wider classes of subjects from which the experimental work has drawn a sample.

In work on software engineering, this is a particularly important threat to validity of findings because of the wide range of diverse programs available to any study of their properties. In the experiments reported upon here, this threat to validity is somewhat mitigated by the fact that the study is concerned with a highly abstract representation of a program: the Module Dependency Graph. Since there is a homomorphism that maps many individual programs into a single MDG, the results for a set of MDGs of size C is relevant to a class of programs of cardinally far larger than C.

Nonetheless, as with other empirical studies concerning software, care is required in extrapolation from the results presented in the present paper to the wider class of programs and their weighted and unweighted MDGs. In order to attempt to cater to possible threats to external validity, the empirical study was constructed to use a range of MDGs, both weighted and unweighted, and ranging in size from small to large. The systems under study were also varied in their application types. However, all systems considered came from open source programs and this may affect the degree to which results can be extrapolated. Naturally, it remains possible that nonopen source programs will exhibit different behavior.

Internal validity is the degree to which conclusions can be drawn about the causal effect of independent variables on the dependent variables. In this experiment, potential threats come from inappropriate statistical tests or violations of statistical assumptions, inaccurate underlying analysis, and the degree to which the variables used in the study accurately measure the concepts they purport to measure (a form of construct validity).

In this paper, the choice of subject MDGs and statistical tests was partly governed by the desire to support comparability with other studies. The statistical test used was the t-test. This has been widely used by researchers comparing results from studies of metaheuristic search algorithms. The MDGs studied have also been used in other studies [18], [21], [23], facilitating a degree of comparability.

It is important to use a statistical test for significance of results obtained because there is an inherent degree of random selection in all metaheuristic search algorithms that the experimental result must take into account. It is known that the t-test is best suited to normally distributed data. However, there is strong statistical evidence [9], [24] to suggest that the t-test is robust, even in the presence of significantly skewed and nonnormally distributed data, provided the sample sizes are sufficiently large, which they are in this case.

It is also important to note that this work neither demonstrates nor implies any necessary association between quality of systems and the modularization produced by the approach used in this paper. Indeed, module quality may depend on many factors, which may include cohesion and coupling, but which is unlikely to be limited to merely these two factors.

8 Conclusion and Future Work

This paper introduces the multi-objective approach to software module clustering. It introduced two multi-objective formulations of the multi-objective problems and presented results for the application of these techniques, comparing the results obtained with those from the existing single-objective formulation on 17 real-world model clustering problems

The results indicate that one of the two approaches, the Equal-size Cluster Approach, is able to produce better solutions than the existing single-objective solution, both in terms of the multiple objectives it aims to satisfy, but also in terms of the single objective upon which all previous work has focused. This improved performance comes at a significantly increased computational cost. For problems in which the software engineer is prepared to wait for the optimal reclustering of their system, the multi-objective approach therefore has considerable merit.

The multi-objective approach lends itself to extensions to consider other possible objectives with respect to which modularization could take place. Future work could consider such additional objectives. For example, we could consider the footprint size of each module, the communications bandwidth (not merely number of inter-edges) the location of features found in module. Future work should also consider the degree to which different approaches produce different kinds of clustering and the underlying reasons for the difference in the results obtained using the ECA and MCA approach.

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